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A model calibration framework for simultaneous multi-level building energy simulation

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HIGHLIGHTS

- Introduce a framework for multiple levels of building energy simulation calibration.
- Improve the performance reliability of a calibrated model for different ECMs.
- Achieve high simulation accuracies at building level, ECM level and zone level.
- Create a classification schema to classify input parameters for calibration.
- Use evidence and statistical learning to build energy model and reduce discrepancy.

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ABSTRACT

Energy simulation, the virtual representation and reproduction of energy processes for an entire building or a specific space, could assist building professionals with identifying relatively optimal energy conservation measures (ECMs). A review of current work revealed that methods for achieving simultaneous high accuracies in different levels of simulations, such as building level and zone level, have not been systematically explored, especially when there are several zones and multiple HVAC units in a building. Therefore, the objective of this paper is to introduce and validate a novel framework that can calibrate a model with high accuracies at multiple levels. In order to evaluate the performance of the calibration framework, we simulated HVAC-related energy consumption at the building level, at the ECM level and at the zone level. The simulation results were compared with the measured HVAC-related energy consumption. Our findings showed that MBE and CV (RMSE) were below 8.5% and 13.5%, respectively, for all three levels of energy simulation, demonstrating that the proposed framework could accurately simulate the building energy process at multiple levels. In addition, in order to estimate the potential energy efficiency improvements when different ECMs are implemented, the model has to be robust to the changes resulting from the building being operated under different control strategies. Mixed energy ground truths from two ECMs were used to calibrate the energy model. The results demonstrated that the model performed consistently well for both ECMs. Specific contributions of the study presented in this paper are the introduction of a novel calibration framework for multi-level simulation calibration, and improvements to the robustness of the calibrated model for different ECMs.

1. Introduction

Buildings account for one-third of the total global energy consumption [1]. In the commercial building sector, more than 80% of building energy consumption occurs during the operation phase [2] to maintain indoor environments and provide building-based services. By analyzing the differences between actual energy consumed and energy required to satisfy building operation demands, it is found that up to 30% of thermal energy and 13% of electrical energy could be saved if energy conservation measures (ECMs) were to be adopted in office buildings [3]. Simulation, the virtual representation and reproduction of building energy process, is widely used for integrating heat and mass transfer, environmental data, and load-HVAC interactions, as well as generating periodical

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energy performance estimates for building systems, such as HVAC (heating, cooling and air conditioning) systems [4–6]. Compared to field experiment, simulation has several advantages: (1) simulation allows analysts to evaluate the system performances when field experiments are infeasible; (2) simulation facilitates the investigation of various ECMs before being implemented; (3) simulation is less expensive and less time consuming; (4) simulation can be reversed after implemented; (5) simulation could control factors that cannot be controlled in a field experiment (e.g., weather conditions); (6) simulation is non-intrusive for a building and its occupants; (7) simulation outputs different performance indicators, which are hard to be metered in field experiments; and (8) simulation makes it easier for analysts to interpret results.

Despite its advantages, expected energy savings from relatively optimal ECMs reported in simulations do not usually match those measured in actual buildings due to the discrepancies between actual buildings and their virtual representations. Empirical studies have revealed noticeable differences between simulation results and actual measurements [7,8]. Simulated results sometimes deviate significantly from the measured ones [9]. Only if a simulation model can generate outcomes that closely match the measured energy performance of a building, it has potential to be reliable and representative in its ability to accurately estimate energy savings from different ECMs. The accuracy of a simulation model largely depends on how well the outputs are compatible with available measured data, which in turn depends on how accurate the inputs could empirically reproduce the properties of a building the model simulates [10].

In general, energy model calibration is an over-parameterized and context-related process. The model calibration is commonly defined as an inverse approximation because of the need for tuning necessary inputs to reconcile the outputs by a simulation program, as closely as possible to the measured energy data. It is over-parameterized because of the large number of independent and interdependent input parameters to be specified, which represent the complex correlations and dynamic interactions among envelope thermal conditions, HVAC responses, exterior impacts (e.g., solar radiation) and interior impacts (e.g., light related heat gains). They cannot always be determined by available evidence in calibration. Two sources are recognized to be generally responsible for discrepancies in building energy simulation. One is the uncertainty in input parameters and the other one is the simplification of building and building systems, assumptions of thermal processes, and algorithmic differences used in simulation programs [11,12]. Since the second source of error depends on the simulation program chosen, this paper focuses on the first source of error: reducing the discrepancies in outputs caused by the uncertainty of input parameters. Quality of the calibration is limited by the determination of input parameter values, which represent the building as abstraction in a simulation. Therefore, simulation is a context-related process.

Current calibration methods focus on single-level simulation accuracy. Single level of calibration considers the accuracy for one scale of output in an energy simulation, such as building level gas consumption or zone level electricity consumption. Since there are a large number of input parameters but few output variables (depending on the required resolution and the length of simulation), it is usually relatively easy to approximate high accuracy for a single level of simulation. However, simultaneous accuracy for multiple levels of simulation is crucial. For example, building level accuracy could provide an insight about overall energy performance of a building and building systems; ECM level accuracy could represent the direct energy consequences of applying a certain type of energy conservation measure, and is important for guiding further research and practice towards more energy-efficient controls; zone level accuracy could decompose energy consumption by a zone that is the control unit for heat balance and load calculations, and closely relates to occupant comfort and building system functionality. Although different levels of energy consumptions are interconnected and they reflect the approximation of simulation results to the measured energy performance, accurate simulation of single level does not necessarily mean accurate simulations for other levels, especially when there are several zones and multiple HVAC units in a building [13,14]. It becomes more difficult to achieve high accuracies for multiple levels of simulations simultaneously as the complexity increases due to the complicated and dynamic correlations and interactions among envelope thermal conditions, HVAC responses, exterior impacts and interior impacts. In sum, the research towards studying energy-efficient measures in a building influences more than one level of energy performance and might require other levels of energy simulation for analysis and exploration [15]. Therefore, a multi-level calibration framework is necessary to achieve multiple calibration objectives simultaneously.

This paper introduces and validates a multi-level energy model calibration framework for simultaneously calibrating energy model at multiple levels. To estimate potential energy savings when different ECMs are evaluated, the model has to be robust to the changes resulting from the building being operated differently. This paper uses ground truth energy data from implementations of two ECMs to calibrate the model and demonstrates the model has consistent performance for either ECM. The framework creates a classification schema for parameters (definitions and categorizations of parameters are introduced in Section 3) and integrates the statistical learning based calibration and analytic calibration. It comprises five steps: (1) **initial energy modeling** using available evidence, (2) **sensitivity analysis** to rank the influence of parameters, (3) **parameter estimation** for determining the values of estimable parameters, (4) **discrepancy analysis** to analyze the sources of discrepancies, and (5) multi-objective **discrepancy minimization**. The framework is evaluated using a case study. Simulated HVAC-related energy consumption is compared with the measured HVAC-related energy consumption to validate the proposed calibration framework. The rest of the paper is organized as follows: Section 2 briefly describes the motivation for the proposed calibration framework and discusses the traditional calibration approaches and their disadvantages; Section 3 outlines the objectives and methodology of the paper. Section 4 describes how the case study model is calibrated using the proposed framework, and Section 5 analyzes the case study results and discusses the limitations. Finally, Section 6 concludes the paper.

2. Building energy model calibration

Building simulation could be error-prone because of the complex correlations and dynamic changes in envelope thermal conditions, exterior impacts (e.g., solar radiation) and interior impacts (e.g., light related heat gain), as well as because of the large number of independent and interdependent input parameters, which cannot be all obtained empirically [11]. The time and effort required to collect data and determine input parameters make energy model calibration a challenge for large-scale applications [16].

Considering the fact that ECMs are specifically designed for appointed buildings, each building has to be modeled and calibrated individually. Using typical/standard values for input parameters or estimating energy performance based on similar building data does not provide accurate energy model calibration for another specific building [17]. A review of current calibration works has revealed that there is no generally adopted methodology, by which building energy models should be calibrated [18,19] due to the different requirements for simulations, different purposes of simulations, different configurations of building systems, different available evidence and different levels of knowledge and experience of analysts. Below is a review of major calibration approaches found in recent literature.

Statistical learning based calibration methods apply a simple or multivariable mathematical/analytical analysis to find relationships among actual measurements, simulation outputs and input parameters. A simple way to express a statistical relationship is by an objective function or a penalty function [20,21], in which input parameters or output variables are assigned certain weights, and a mathematical/analytical algorithm is then used to map them with actual energy measurements. Input parameters could be either static parameters (e.g., chiller coefficient of performance) or dynamic parameters (e.g., room temperature). The weights are determined using measured data, such that the corresponding formulation is able to predict acceptable energy performance with no direct link to physical building properties [22]. Statistical relationships could also be established by machine learning techniques [23–25]. Once the learning models are built and tuned, they can be applied to process new model inputs and estimate corresponding energy performances. Supervised machine learning techniques, such as Artificial Neural Network (ANN) [26] and fuzzy logic model [27], which are capable of modeling complex relationships between inputs and outputs, are commonly used to learn sophisticated non-linear and joint effects of input parameters [28]. In view of the large number of parameters to be considered, learning model training is computationally expensive and may not provide acceptable solutions because of overfitting (overspecialization and cannot be generalizable). In addition, energy model calibration is a case-by-case process; machine-learning models generated from reference buildings may not be applicable to other buildings, even they might be in the same climate.

In general, statistical learning based calibration requires a short development time and provides an accurate estimation of energy consequences given the availability of prior training data. However, it is data-driven and requires extensive data for retraining if there are any system operational changes. Moreover, a statistical learning based calibration method abstracts the calibration process to a pure mathematical fitting problem, which may not be able to represent the real function or contribution of each input parameter to building energy performance. Even though the net effect of all parameters can generate outputs that closely match the measured energy performances, the individual parameters may still be incorrectly or unreasonably tuned, thus it is difficult to simultaneously achieve high simulation accuracies at multiple levels.

Analytical calibration methods use available evidence, such as zone size and window height, to iteratively adjust input parameters based on analysis, experiences and trial until simulation outputs match actual measurements. This calibration method is mostly manual, iterative and pragmatic intervention, which requires significant time, effort and expertise [29,30], however it is capable of modeling a building and building systems under previously unobserved conditions. Standard steps (e.g., simulation plan, data collection, evidence input, calibration, model refinement) have been widely used in previous research [31–33], and the process typically requires conducting interviews, collecting drawings, specifications, field measurements, logs, system manuals and system settings [34–36]. To improve model calibration, using continuous field measurements and observations, has been proposed and the calibration accuracy was significantly increased [37]. Sensors could also be installed to get the necessary information for calibration [38]. For parameters that cannot be determined directly from evidence, expert knowledge and experience are required. Most simulation exercises employ heuristic methods for parameter estimation. Specifically, an expert first selects a set of parameters that are likely to significantly influence the outputs of a simulation model on a building-to-building basis [10]. Different combinations of values are then tested until differences between the simulated and measured energy performance are reasonably small.

Analytical calibration methods require a trial and error process, where there are large numbers of parameters. It may not be reliable as the complexity of the simulated building increases. Even if each input parameter is empirically validated, the simulation output of a building may still be far from measured building performance, since buildings do not always behave as initially designed. Continuous updates for input parameters are required for calibration. Quality of the analytic calibration model relies heavily on the subjective judgment of an analyst on building systems and thermal processes, especially in the choice of parameters to be calibrated, quantification of their prior distribution, best-guesses of parameter estimation, and interrelations among parameters. High accuracy at multiple levels is difficult to be achieved solely with this method.

More recently, an integration of analytical calibration methods and sensitivity analysis or analytical optimization approaches has been introduced [39]. Sensitivity analysis is widely used to reduce the number of parameters to be adjusted [40]. A matrix of possible values of each input parameters is created using sampling algorithms, and imported to a quasi-deterministic approach, such as the Monte-Carlo (MC) method. After thousands of simulation trials by a commercial simulation program a set of promising vector solutions is found rather than a single one based on goodness-of-fit [41,42], or an analytic meta-model is obtained to minimize the difference between simulated and measured data [43]. However, the performances of integrated calibration methods highly depend on the possibility that the solution exists in the trials.

Integrated calibration is computationally efficient and could provide comparable results [11]. Usually a group of solutions are selected with actual energy measurement being within a range of the values simulated. However, there is no work to date that specifically focuses on a solution with high accuracy for multiple levels. Sometimes zone level energy consumption is simply added up to represent building level or system level energy consumption [13,14]. These sequential calibrations cannot achieve simultaneous high accuracy for multi-level simulations when there are several zones and multiple HVAC units.

3. Objectives and calibration methodology

An energy model that has high simulation accuracy at multiple levels could provide reliable estimation of energy consequences of different ECMs (energy control measures) in a building. Therefore, the first *objective* of this study is to introduce a multi-level calibration framework for building energy simulation. In addition, in previous work, simulation is calibrated with ground truth collected under a certain ECM. These calibrated models do not necessarily reflect the energy implications under other ECMs. An energy model that is robust to the changes resulting from a building operated under different ECMs could provide credibility to compare the potential energy savings obtained from different ECMs and could help researchers/practitioners to choose the relatively optimal ones for implementation. Therefore, the second *objective* of this study is to improve the robustness of energy simulation. Specifically, in this study, the ground truth energy data for calibrating the energy model are mixed from two controls (two different

ECMs) and the hypothesis that the model would have consistent performance for either of the ECM is tested.

Since an energy simulation model typically has large amounts of input parameters that cannot be all determined by available evidence, and may result in deviations and confusions for determining values, a classification schema is created and all of the input parameters are classified into hierarchical categories for calibration. First the input parameters are classified into two categories: observable parameters and non-observable parameters (Fig. 1). **Observable parameters** are the parameters, such as window sizes and equipment multipliers, whose values could be determined directly using available evidence, such as evidence gathered through archived documents or on-site visits. **Non-observable parameters**, such as material conductivity and fan efficiency, cannot be determined by the available evidence. They are analyzed by sensitivity analysis, based on which the influential ones are differentiated and further categorized as estimable parameters and adjustable parameters. **Estimable parameters** are the non-observable parameters that are deterministic in nature (e.g., door open/close status) but whose values are difficult to collect due to lack of feasible data collection approaches or privacy concerns, for example, occupancy schedules. In this study, it is assumed that estimable parameters could be indirectly inferred or calculated using observable parameters by learning the relationships between estimable parameters and observable parameters. **Adjustable parameters**, such as light radiant fraction, are parameters that are stochastic in nature. The values of these parameters are varied in their respective domains and cannot be measured exactly.

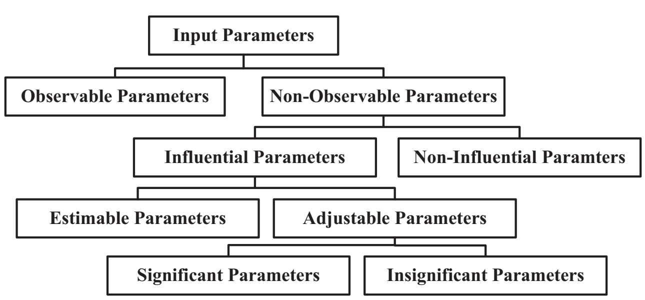

Fig. 1. Classification schema of input parameters.

Further, adjustable parameters are divided into **significant adjustable parameters** and **insignificant adjustable parameters** based on their statistical significance. It is assumed that the significant adjustable parameters are mainly responsible for the discrepancy between the simulated and measured energy performances. Their values should be carefully determined for multi-level simulation calibration. The multi-level calibration is defined as a calibration that minimizes discrepancies at different levels of simulation (e.g., building level, ECM level, and zone level). It is important to note that this classification only defines the characteristics and functions of each category for input parameters since building energy model calibration is a unique process. The specific members vary case by case.

Our framework is built on the following tasks: gathering data, constructing the model, simulating the model, analyzing and minimizing discrepancies between the simulated and measured energy performances. The framework has five consecutive steps (Fig. 2): (1) initial energy modeling using available evidence; (2) sensitivity analysis, which ranks and compares the influences of non-observable parameters on the energy simulation outputs at multiple levels; (3) parameter estimation to determine the values of estimable parameters, such as occupancy schedule, and to finalize base modeling; (4) discrepancy analysis, which assists to understand the sources of discrepancies between the simulated and measured energy performances; and (5) discrepancy minimization, the last step, aims to reduce discrepancies at multiple levels simultaneously by determining the parameter values that cannot be obtained through evidence or estimation. The proposed calibration methodology uses evidence to build the energy model and implements statistical learning to reduce the simulation discrepancy. Our detailed methodology is described step-by-step in the following subsections.

3.1. Initial energy modeling

The goal of this first step is to provide a basic description for building geometry, construction elements and mechanical systems, using evidence-based data. The initial representation of the energy model is created through iterative model evolution, where each input is updated based on a source of evidence. Since there may be various available sources for determining parameter values, the hierarchy structure described in the literature [31,36,44]

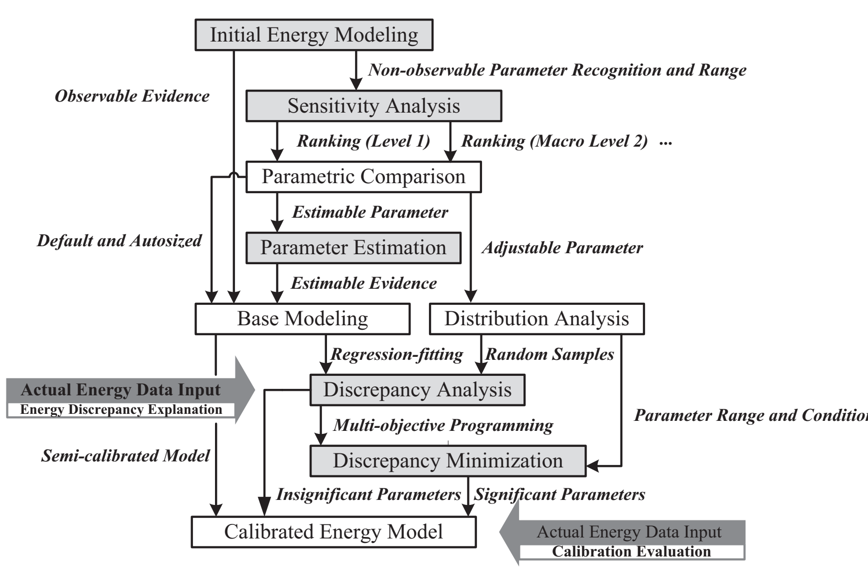

Fig. 2. Proposed energy model calibration framework.

is used to rank evidence sources. The source with higher priority is considered more reliable than the lower one (Fig. 3). In general, the first step is to evaluate the as-built and design documents, including architectural plans, electric lighting systems (e.g., lamps and ballasts), HVAC designs (e.g., zoning and connections), schedules (e.g., designed occupant schedules and light schedules), inventories (e.g., appliances and equipment), and HVAC specifications (e.g., fan nominal power). This step integrates both as-built data and as-designed assumptions. The second step is to visit site, survey and interview the technicians, engineers and building facility management personnel, and study the operation and maintenance (O&M) manuals, as well as conduct some continuous measurements, such as lighting level if possible (depending on specific building situations and available methods). In this step, the data collected from the first step is re-examined to check whether there is an update to be made or there is any change since the building was built. The last step is using default settings based on similar types of buildings in simulation programs and using the codes and standards when needed. Although research has demonstrated that the data from ASHRAE standards and manufacturer handbooks are not reliable due to the substantial variability in buildings and building systems, values must be set for all input parameters to maintain model integrity. Here, modeling steps do not necessarily follow the hierarchy direction (Fig. 3). Since the available evidence for different buildings may have different levels of details and accuracies, typically the initial modeling can be described as an ad-hoc procedure, requiring numerous iterations of input updates. It is difficult to determine a specific evidence source for a specific parameter, however basically the initial modeling accuracy increases if more high-level evidence is used for determining the values of input parameters.

In general, lack of necessary evidence for determining the input parameters is common in building energy simulation and that is one of the motivations for this study. The evidence should be used if possible. For those parameters that cannot be determined directly by evidence, in our calibration framework, values are first assigned as default values or autosized by the simulation program, while the influential ones are classified into two categories of estimable parameters and adjustable parameters for further analysis. Once the new values are calculated, we use them to update the temporary values set in the initial modeling.

3.2. Sensitivity analysis for parameters

The initial model is then used as a basis for the sensitivity analysis. Usually, there are several hundred non-observable parameters whose exact values are unknown and it is usually

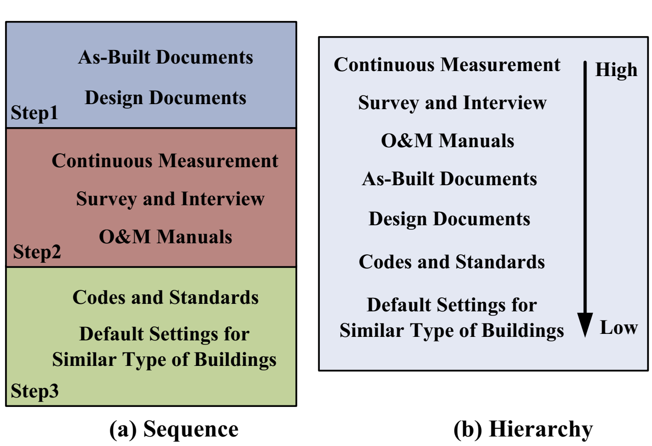

Fig. 3. Hierarchy and sequence for observable parameter determination.

infeasible to run millions of simulations to determine the values of all of them with an equal priority. Therefore, the number of non-observable parameters to be studied should be reduced. Given the fact that the influences of certain input parameters on energy simulation results are more significant than the others; these inputs should be prioritized for model calibration. In our calibration framework, sensitivity analysis is used as a screening method to rank non-observable parameters based on how the simulated energy performance would change in response to the changes made to each non-observable parameter. In order to achieve accurate energy simulation results at multiple levels, a sensitivity analysis is conducted for n times to account for n levels of energy consumption.

There is no established rule or procedure for sensitivity analysis, as each method has its own pros and cons [45]. We use Morris method in our framework to identify the influential parameters, as it has been proven to be a valid method for screening building energy simulation parameters [46]. Morris method makes no assumptions about the relationships (e.g., linearity and correlation) between parameters and model outputs [47]. It could process large numbers of parameters equally by a relatively limited number of simulation runs. This process is efficient and accurate as it does not require a predefined probability density function for each parameter [47], given the fact that assigning estimated probability density functions for hundreds of non-observable parameters is time-consuming and error-prone. Although Morris method cannot provide exact uncertainty that each parameter causes, it is sufficient for ranking the influences and selecting parameters for further adjustment. In addition, different parameter types (e.g., discrete, continuous or multi-dimensional) could be considered equally. Morris sensitivity analysis is based on the factorial sampling technique, in which the influential input parameters are identified through a series of simulation runs by changing one parameter at a time, and then comparing the corresponding simulated energy performances. A number of individual one-factor-at-a-time samples of input parameters are randomly generated within their ranges as an input vector for simulations. In our framework, we use larger ranges to be conservative, because the proper range of a parameter is determined by analysts' knowledge and experience, and if the range is larger, the probability that the actual value within the range is high. Sensitivity of each parameter is expressed by a value called "elementary effect" [47], which is defined as the measure of parameter influence, showing the change in the simulation output as a result of a change in this parameter, while all other parameters are kept constant. As the value of each parameter is varied within its range, the mean value of the effect m is then compared to the standard deviation S_d to provide a normalized criterion for ranking influential parameters. Parameters with higher absolute mean-standard deviation ratio are more influential. The boundary between influential parameters and non-influential parameters should be determined case by case based on different goals, computational requirements and result distributions. Based on the demonstration by previous research [46], if the parameters are above the threshold set by the lines $m = \pm 2S_d/\sqrt{r}$ (r is the number of independent samples for each parameter), they are considered to have non-linear or joint effects. When the sensitivity analysis is completed, the influential parameters are explored in the next steps while the non-influential parameters are assigned with default values or autosized by the simulation program.

3.3. Parameter estimation

Parameter estimation is conducted for the influential non-observable parameters that are deterministic in nature, however are difficult to be collected due to lack of feasible data collection approaches. These parameters could be building use related (e.g., occupancy, lighting, and appliance) or system operations related (e.g., HVAC thermostat schedules). Prior research has demonstrated that occupancy is one of the important factors for the discrepancies between the simulated and measured energy performances [8], as the main end-users of energy such as HVAC systems, lighting and appliances are associated with occupancy [48,49]. Traditionally, the use of day-typing (typical days to characterize a period of time) and zone-typing (typical space to represent a building) were adopted. Currently observations, surveys, short-term measurements or real-time end use monitoring methods are used to collect data instead. However, these methods are not practical due to the intrusion they cause to buildings and their occupants, and they do not satisfy the requirements for detailed building energy simulation because of the lack of precision and consistency and verification in auditing.

In this paper, the tested hypothesis is that some of the estimable parameters could be indirectly inferred or calculated from the observable parameters. This step is specific for each case, however the underlying assumption remains the same: the parameters to be estimated either have regular influences on certain observable parameters or their values repetitively occur with variations. Therefore, the relationships between estimable parameters and observable parameters could be established through statistical learning. Once completed, measurements of observable parameters (depending on the sophistication of building management systems and types of onsite metering systems) are learned as parameter values for estimable parameters. If there are common parameters shared by different levels, they are assigned with the same values. Although varies case by case, the parameter estimation step is a mining process to find the patterns of unknown parameters related to building use and system operations using known parameters. In order to test the hypothesis that a consistent simulation performance can be achieved when the model is calibrated using ground truth energy data from mixed ECMs but it is simulated for an individual ECM, the ECM-related parameters should be controlled instead of being estimated.

3.4. Simulation discrepancy analysis

Since the influential parameters are the main sources of the discrepancies, and the estimable parameters could be indirectly estimated using evidence related data, which are deterministic and based on the facts, it is assumed in this paper that some of the adjustable parameters are responsible for the majority of the discrepancies between the simulated and measured energy performances. Therefore, we propose to explore the structural patterns of the discrepancies and screen out insignificant parameters. Several methods could be developed to analyze the patterns, however as a beginning, the linear relationship is explored to model the contribution of each adjustable parameter to the discrepancies using a regression fitting. All adjustable parameters are varied within their ranges and the nominal values are their default values that could be found in simulation programs. A probability density function (e.g., triangular, Gaussian, or uniform) of each continuous parameter, such as wind speed, is used to select the values based on its probability distribution, while discrete parameters such as iteration number are characterized by minimum, maximum and default values. If analysts cannot determine the ranges, or when there are time constraints, preferred ranges of parameters, provided by the simulation programs, could be used instead. Otherwise, analysts could narrow down or specify the range of each input parameter. Each parameter is normalized by $x^* = \frac{x - x_{\min}}{x_{\max} - x_{\min}}(x^*_{\max} - x^*_{\min}) + x^*_{\min}$ for comparison.

Random sampling is used to select samples to form independent variables, and multiple simulation runs are then completed to generate the output vector. The discrepancies between the simulated and measured energy performances, calculated by dividing the difference between the simulated results and the actual measurements by the actual measurements, are used as dependent variables. The values of remaining parameters (after parameter estimation is completed) are considered as independent variables. The number of simulation runs is usually based on experience or trial; however in our framework, the actual number of simulation runs depends on when the regression model converges. Specifically, multi-regression is used to establish the linear model, the outputs (discrepancies) of which are the sums of combinations of parameter values, while the weights are assigned to each parameter before adding them together. The regression line is denoted by $y_{\text{level}n} = a + b_1x_1 + b_2x_2 + b_3x_3 + \ldots + b_kx_k + \varepsilon$, where a is the intercept, ε is the random disturbance and b_i is the coefficient of the ith parameter, indicating its contribution to the determination of the dependent variable. If some of the parameters are proven to be interrelated as a result of the sensitivity analysis, the linear model is modified into a non-linear one. For example, if parameter $x_1,\ x_2,\ x_3$ are all above the $m = \pm\frac{2S_d}{\sqrt{r}}$ lines (for each parameter, m is the mean of its elementary effects, S_d is the standard deviation of its elementary effects, and r is the number of samples selected), the new multi-regression model would be $y_{\text{level}n} = a + b_1x_1 + b_2x_2 + b_3x_3 + b'_1x_1x_2 + +b'_2x_2x_3 + b'_3x_1x_3 + b'_4x_1x_2x_3 + b_4x_4 \ldots + b_kx_k + \varepsilon$ to take their interactions into consideration. In order to calibrate the energy model at multiple levels, n (n equals to the number of levels) multiple-regression models are created simultaneously, in which some of the parameters might be shared. The same parameters could have different weights or even reverse contributions (overestimate or underestimate) to different levels of simulations. The intercepts and coefficients of variables are estimated with the least square method, and coefficients of determination ($\bar{R}^2$) are calculated to interpret the proportions of discrepancies that can be explained by the regression models. F-statistics is used to test the significance of the regression models and to analyze whether the discrepancies are significantly influenced by the adjustable parameters. Then T-statistics is used to differentiate insignificant parameters from significant parameters, which account for the discrepancies.

3.5. Simulation discrepancy minimization

After identifying the contributions of parameters to the simulation discrepancies at different levels, the most important step is to determine the values of these parameters for minimizing the discrepancies at multiple levels simultaneously. In current practice, the values of the significant adjustable parameters are usually determined as best-guesses of experts or adjusted blindly. In order to make this step more efficient and repeatable, multi-objective programming, commonly used in optimizing energy efficient designs [50], is used for updating the values of adjustable parameters and minimizing the simulation discrepancies at multiple levels simultaneously. In our framework, the multi-objective is denoted by $\min = \{y'_{\text{Level1}}, y'_{\text{Level2}}, y'_{\text{Level3}}, \ldots, y'_{\text{Level}n}\}$, subject to the constraints, such as bound limits and integrality requirements. Since the values of all parameters should be selected from their parameter ranges and are recommended not to be far from the default values set by the program, the objective functions are expressed as $y'_{\text{level}n} = a + b_1x_1 + b_2x_2 + b_3x_3 + \ldots + b_kx_k + \varepsilon + \sum_1^k (x_k - x_{\text{k default}})^2$ (both x_k and $x_{\text{k default}}$ are normalized by $x^*_{\text{k or k default}} = \frac{x_{\text{k or k default}} - x_{\min}}{x_{\max} - x_{\min}}(x^*_{\max} - x^*_{\min}) + x^*_{\min}$ where a penalty is introduced. At first, each single objective function is solved independently. Pareto optimal solution sets A^{*} (for minimizing discrepancies at the level 1), A^{**} (for minimizing discrepancies at the level 2), and so forth, are generated separately for multiple objectives. The union of A^{*}, A^{**} and so forth, is the solution set for the multi-objective programming. The relative importance of the n objectives should be carefully selected based on the purpose of simulation, as the selected weights have significant influences on the final solution [51]. If the weights are arbitrarily assigned, the programming may converge on the locally optimal solution. Therefore, in this paper the weight computation process is transformed to a synthetical fitness optimization problem with preference being considered as a constrain condition. Analysts should determine the relative importance of w_1^0 (for level 1 accuracy) and w_2^0 (for level 2 accuracy), and so forth. (e.g. $w_1^0 > w_2^0 > w_3^0 > w_4^0 \ldots > w_n^0$). Gradient projection method [52] is then used to search the optimal weights that could maximize weighted variance and differentiate each solution from others. Once the weights are decided, they are assigned to all objectives, and the multi-objective is converted into a single weighted objective function as $\min f = \{w_1^0 y_{\text{Level1}} + w_2^0 y_{\text{Level2}} + w_2^0 y_{\text{Level3}} + \ldots + w_2^0 y_{\text{Level}n}\}$, where $w_1^0 + w_2^0 + w_3^0 + \ldots + w_n^0 = 1$. Linear programming is then used to synergize the weights of parameters at each level determined by regression analysis and find the initial solutions (seed vertex). An effective vertex near the seed vertex is also searched. As long as the actual disaggregated energy performance for detailed end uses, such as lighting, equipment, and HVAC, could be metered, the multi-objective discrepancy minimization method could be applied to any multiple-level calibration.

4. Framework evaluation

While Section 3 provides a step-by-step description of the proposed calibration methodology, Section 4 evaluates its validity by using a case study, as explained below. However, it is important to note that the contribution is the calibration framework, introduced in this paper, rather than the case study results, which are used to evaluate and validate the framework.

4.1. Case study description

A typical educational office building, located on the University of Southern California campus, was chosen to implement the proposed calibration framework. The case study building (Fig. 4) is a three-story office building with a gross area of 3735 m^2, and contains 89 mechanically ventilated rooms that have spaces of varying sizes and functions. Most of the rooms in the building are enclosed single occupancy offices; other rooms are classrooms, conference

Fig. 4. Case study building.

rooms, and auditoriums. The building hosts approximately 50 permanent occupants (i.e., staff, faculty, graduate students). The building is equipped with a state-of-the-art Building Management System (BMS) and central HVAC system with air handling units (AHU). A zone in this paper is defined as the mechanical zones for the HVAC system. The 89 rooms are divided into 67 mechanical zones, including 64 VAV controlled zones and 3 Fan-Coil controlled zones. The heat flow and ventilation of each zone can be individually controlled and adjusted. There are two AHUs in the building, each servicing one side of the building with similar sizes of service areas.

The HVAC energy consumption in the building can be decomposed to primary HVAC systems, such as used by chillers and boilers to generate chilled and hot water, secondary HVAC systems, such as used by AHUs and their embedded fans to distribute conditioned air in the building, and HVAC terminals, such as VAVs and FCUs. The ground truth energy data used for calibration was obtained or calculated from the information recorded by a Honeywell Building Management System (BMS), which provides central control over the chiller, boiler, AHUs and VAVs. This information typically includes AHU damper position, fan flow rate, outside temperature, VAV damper position, supply air temperature, return air temperature, and so on. OpenStudio and EnergyPlus programs were used for energy simulation. OpenStudio accounts for geometrical modeling and acts as a middleware to connect with EnergyPlus [53]. Detailed energy modeling and calibration are done in EnergyPlus as it could provide strict heat balance and a simultaneous solution for LSPE (load, system, plant, economic).

ECM, which stands for energy conservation measure, refers to a specific HVAC control strategy in this paper. Two different ECMs were implemented in the test bed building, in order to explore our second objective and test our hypothesis, which is an energy model calibrated using ground truth energy data from mixed ECMs could consistently simulate energy performance for either ECM. The first ECM (baseline HVAC control strategy, short as "**baseline ECM**") ran at an on-hour mode during the daytime (6:30–21:30 on workdays, and 7:00–21:30 on weekends), all mechanical zones in the building were assumed to be always occupied, and a constant temperature setpoint (22.8 °C) was maintained by a Proportional Integral Derivative (PID) controller, which dynamically adjusted the airflow damper and reheating valve of each zone. The second ECM (bimodal HVAC control strategy, short as "**bimodal ECM**") was demand responsive and based on real-time occupancy. During the daytime, an occupied mode was enforced for occupied zones, where a constant temperature setpoint (22.8 °C) was maintained by the PID controller. If a zone was vacant for a minimum of 15 min, a vacant mode was enforced, where the temperature setpoint was set back to 25.5 °C until the zone was occupied again. The bimodal ECM was implemented on the east side of the second and third floors covering 37 rooms (14 zones of which were metered by the BMS). The rest of the building was operated using the baseline ECM. Both ECMs had off-hour modes, where the HVAC system was shut off during nighttime, and no cooling, heating or ventilation services were provided. Only minimum airflow was maintained to meet the ASHRAE compliance. Four months of energy consumption data were collected during these two periods. The first period spanned for 82 days from Jan 1st to Feb 21st 2013 and from Apr 1st to Apr 30th 2013, and the HVAC system during this period was operated under baseline ECM. The second period spanned for 38 days from Feb 22nd to Mar 31st 2013, when the bimodal ECM was adopted for the 14 zones.

4.2. Evaluation matrices

HVAC related energy consumption was simulated to validate the proposed calibration framework at multiple levels as explained

Table 1
Acceptable tolerances for hourly building energy simulation.

Metric	IPMVP (%)	FEMP (%)	ASHRAE (%)
MBE	±5	±10	±10
CV (RMSE)	±20	±30	±30

below. It is important to note that even though the framework is evaluated at three different levels (i.e., building level, ECM level and zone level energy simulation calibration), the discrepancy minimization could be applied to any multiple levels of calibrations, such as floor level. A total of 22 zones and HVAC chiller, boiler and AHUs were taken into account for validation. Metrics were defined to explore the discrepancies between the simulated and measured HVAC energy consumptions at three different levels. For the **building level** calibration, the sum of electricity and gas consumed by the entire HVAC system, including the air loops and plant loops, was compared with the measured consumption to indicate the percentage of building level discrepancy. Energy consumption of each zone for each day, including heating and cooling provided by the terminals for actual conditioning demands, was calculated by a heat formula (Eq. (1))

$$Q_i = \int^{\rho} \dot{V} C_{pi} |T_{si} - T_{ri}| \tag{1}$$

where T_{si} and T_{ri} are supply air temperature and return air temperature for zone i, and $\dot{V}$ is the air volume flow rate (m^2/s). Their actual values are metered and recorded by BMS. C_{pi} is a constant value of specific heat capacitance for zone air as 1000 J/(kg °C) and ρ is the zone air mass density with the value of 1.29 kg/m^3. Zone level ventilation was not considered in this paper due to the lack of metered data.

The **ECM level** energy consumption was calculated by adding the energy consumptions of the zones served by one AHU (Eq. (2)). The AHU takes in outside air, mixes it with returned air from the building, and cools down the mixed air to 12.8 °C with chilled water supplied by the chillers. There are 14 zones on the east side of the second and third floors, where both the baseline ECM and bimodal ECM were implemented.

$$\overline{Q} = \sum_{i}^{14} Q_i \tag{2}$$

The **zone level** energy consumption was calculated by averaging the energy consumptions of 8 zones on the west side of the third floor where only baseline ECM was implemented (Eq. (3)).

$$\overline{Q} = \frac{1}{8}\sum_{i}^{8} Q_i \tag{3}$$

The MBE (mean bias error) and CV (RMSE) widely used in previous research [8,36,37] were chosen as two criteria to evaluate the calibrated energy model by checking whether there is acceptable agreement between the simulated and measured energy consumption. Hourly calibration was conducted. N stands for the number of hours within a period. E_{actual} is the actual energy consumption metered by the BAS while $E_{simulated}$ is the simulated energy consumption by the building energy model (Eqs. (4) and (5)).

$$\text{MBE} = \frac{\sum_{j=1}^{N}(E_{\text{actual}(j)} - E_{\text{Simulated}(j)})}{N} \tag{4}$$

$$\text{CV(RMSE)} = \frac{\sqrt{\sum_{j=1}^{N}(E_{\text{actual}(j)} - E_{\text{Simulated}(j)})^2}}{\overline{E}} \tag{5}$$

MBE is a non-dimensional bias measure for overall deviation (Eq. (4)). A negative MBE value means the simulation model underestimates the energy consumption, while a positive MBE value represents an overestimation. It could measure long-term model performance through analyzing the error between the simulated and measured energy consumptions; however the underestimation and overestimation might compensate each other. The averaged sum of squares errors is called the mean squared error (MSE). Coefficient of variation of RMSE (CVRMSE) is determined by dividing the RMSE by the mean measured energy consumption (Eq. (5)). It is not influenced by the compensation effect and could evaluate the variability of agreement between the simulated results and measured values over a period of time. In general, an energy simulation model is considered as calibrated if the two criteria are satisfied at all the three levels according to the acceptable tolerances set by ASHRAE Guideline 14, IPMVP or FEMP [54–56]. As there is no regulated daily tolerance in literature, in this case study, hourly tolerances (Table 1) were used for evaluating daily MSE and CV (RMSE).

4.3. Initial energy modeling

The initial energy model, for the case study, incorporated information collected from archived documentations, such as as-built drawings, specifications, renovation logs, operating records, and information gathered from on-site visits, where building's geometric characteristics, construction elements, associated mechanical systems, appliance specifications, were collected (Fig. 5). For the rest of the input parameters that did not have available evidence, default settings were used or their values were temporarily assigned according to standards and codes. Weather was modeled using TMY (Typical Meteorological Year) data downloaded from the DOE website (Energy Efficiency and Renewable Energy) specific for the building site [57]. The data were collected from the station close to Los Angeles International Airport that is about 10 miles away from the test bed building. The TMY are data sets of hourly values of meteorological elements and solar radiation for one year. The simulation period spanned from January 1st to April 30th, 2013, and from March 15th to November 15th, 2014.

4.4. Sensitivity analysis for parameters

In total, there were 227 parameters whose values could not be determined (non-observable parameters) during the initial energy

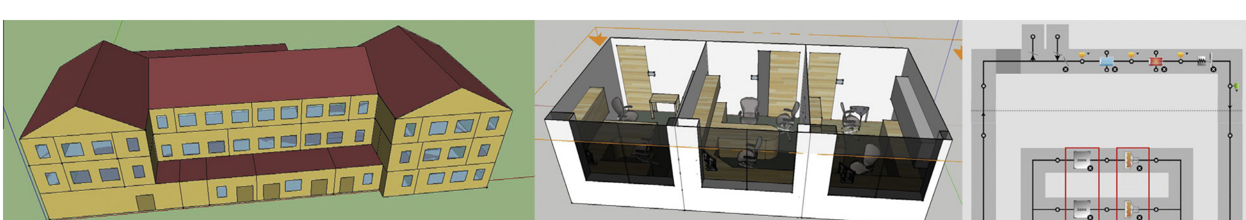

Fig. 5. Building geometry (back side), one typical zone (three offices) and HVAC system.

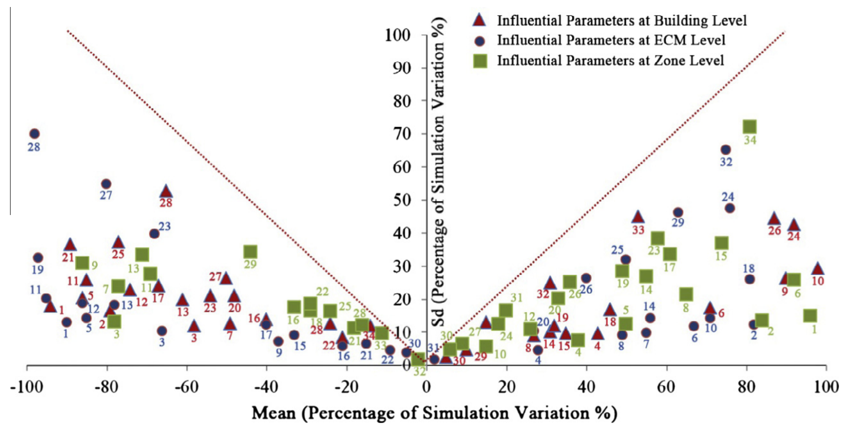

Fig. 6. Mean and standard deviation of the elementary effects on the energy simulation for the influential parameters at the building level, ECM level and zone level.

Table 2a
Influential parameters and their parameter ranges and default values for the building level energy simulation (blue-shaded parameters are for controlling the HVAC system under different ECMs, brown-shaded parameters are estimated based on observable evidence, red shaded parameters are found to be statistically insignificant in discrepancy analysis – explained in Section 4.6).

IDs	Influential Parameters	Parameter Ranges	Default Value	IDs	Influential Parameters	Parameter Ranges	Default Value
1	Chiller COP	0<X<10	5.9	18	Equipment/Appliance Schedule	Estimable	TBD
2	Wind Speed	0<=X<40	15	19	Average Ventilation Rate Range	1<=X<=6	4
3	Occupant Activity	100<=X<=150	115	20	Chiller Part Load Ratio	0.3<=X<=0.9	0.7
4	Heating/Cooling Schedule	ECM Control	TBD	21	Boiler Efficiency	0<=X<=1	0.8
5	Chilled Water Delta T	-50<=X<=50	14	22	Heating/Cooling Time Interval	0<=X<=60	10
6	Solar Absorptance	0<=X<=1	0.7	23	Occupant Heat Load	Estimable	TBD
7	Material Conductivity	0<X<30	17	24	AHU Minimum Airflow Rate	0<X<25000	15000
8	Occupancy Schedule	Estimable	TBD	25	Heat Recovery Efficiency	0<=X<=1	0.8
9	Lighting Fraction Radiant	0<=X<=1	0.72	26	Fresh Air Introduction Rate	20<=X<=50	35
10	Surface Albedo	0<=X<=1	0.3	27	Maximum Zone Wind Speed	0<=X<40	20
11	Fan Total Efficiency	0<=X<=1	0.7	28	Minimum Outside Air Fraction	0<=X<=1	0.3
12	Light Schedule	Estimable	TBD	29	Airflow Convergence Tolerance	0<X<1	0.0004
13	Temperature Sensor Height	0<=X<=3	1.6	30	Lighting Time Interval	0<=X<=60	10
14	Occupancy Time Interval	0<=X<=60	10	31	Ground Temperature	66<=X<=72	68
15	Solar Heat Gain Coefficient	0.25<=X<=0.8	0.5	32	Minimum Surface Convection Heat Transfer Coefficient	0<=X<=5	3
16	Hot Water Sizing Factor	0<X<5	1	33	Ground Reflectance	0<=X<=1	0.2
17	Wall U-Factor	0.2<=X<=1.2	0.8	34	Reference Barometric Pressure	X>0	$1*10^5$

modeling due to the lack of available evidence, such as surface albedo, fan total efficiency and air flow fraction. Morris method was implemented three times for the building level, ECM level and zone level sensitivity analysis. The elementary effect was expressed as a percentage of simulation variation in response to the change resulting from the variation of the input parameter. For each parameter, five independent samples ($r = 5$) were randomly selected and the elementary effects were simulated by EnergyPlus with 1362 simulation runs (the number of runs = $(r + 1)^*$ the number of parameters) in total for each level. The r is usually chosen between 5 and 15. Five samples were chosen for each parameter as the exact rank of parameter sensitivity does not affect the discrepancy analysis and minimization process, thus the minimum number was selected to make the sensitivity analysis efficient. The sensitivity analysis has been implemented using Matlab. The 1362 idf files were generated for simulation runs and the simulation results (from Energyplus) were collected to calculate the elementary effect for each parameter. The parameters were

Table 2b
Influential parameters and their parameter ranges and default values for the ECM level energy simulation (blue-shaded parameters are for controlling the HVAC system under different ECMs, brown-shaded parameters are estimated based on observable evidence, red shaded parameters are found to be statistically insignificant in discrepancy analysis – explained in Section 4.6).

IDs	Influential Parameters	Parameter Ranges	Default Value	IDs	Influential Parameters	Parameter Ranges	Default Value
1	Zone Cooling Sizing Factor	0<=X<=5	1.1	17	Window Shading Coefficient	0.2<X<1.0	0.8
2	Thermostat Setpoint	ECM Control	TBD	18	Fraction of Convective Internal Loads	0<=X<=1	0.7
3	Minimum Airflow Fraction	0<=X<=1	0.2	19	Occupant Heat Load	Estimable	TBD
4	Heating/Cooling Schedule	ECM Control	TBD	20	Airflow Convergence Tolerance	0<X<1	0.0004
5	Temperature Sensor Height	0<=X<=3	1.6	21	Lighting Load	Estimable	TBD
6	Occupancy Schedule	Estimable	TBD	22	Zone Flow Coefficient	0<=X<=1	0.8
7	Heating Coil Efficiency	0<=X<=1	0.8	23	Thermal Absorptance	0<X<0.999	0.9
8	Zone Supply Air Temperature	10<=X<=32	20	24	Infiltration Rate	0.1<X<=5	1.8
9	Solar Heat Gain Coefficient	0.25<=X<=0.8	0.5	25	Gross Rated Cooling Coil COP	0<X<5	3
10	Wall U-Factor	0.2<=X<=1.2	0.8	26	Equipment/ Appliance Schedule	Estimable	TBD
11	Delta Adjacent Zone Temp	-20<=X<=20	10	27	Effective Air Leakage Area	0<X<50	20
12	Occupant Number	Estimable	TBD	28	Light Fraction Radiant	0<=X<=1	0.72
13	Heating/Cooling Time Interval	0<=X<=60	10	29	Maximum Zone Wind Speed	0<=X<=40	20
14	Supply/Zone Air Temperature Delta	-20<=X<=20	6	30	Internal Loads Density	1.5<=X<=3	1.8
15	Daily Temperature Range	-20<=X<=20	10	31	Window Solar Transmittance	0<=X<1	0.7
16	Lighting Schedule	Estimable	TBD	32	Visible Absorptance	0<=X<=1	0.7

then ranked by their absolute mean-standard deviation ratios and the ones with higher ratios were considered as more influential for the energy simulation.

Conservative boundary was set, by which the parameters with absolute mean-standard deviation ratio greater than 0.1 were influential (the boundary could also be determined by experience or using visual plot). Fig. 6 shows the mean and standard deviation of the elementary effects for each parameter. 34 parameters for building level simulation, 32 parameters for ECM level simulation and 33 parameters for zone level simulation were presented in a decreasing order of influence shown in Tables 2a–2c, respectively. The influential parameters for the three levels of energy simulation were not exactly the same; even the common parameters had different orders of influence. As expected, building level influential parameters had global influence on the building energy consumption, basically related to running controls and loads for HVAC systems, conditions and performance for HVAC plants, and envelope thermal characteristics; ECM level influential parameters had influences on local thermal states, loads, control settings and conditions for HVAC terminals; zone level influential parameters were mainly associated with end use demands, material properties, space heat transfer and balance. The three lists of parameters should be given primary focus by changing the values of the influential parameters within their plausible parameter ranges in the next steps. The non-influential parameters were left with their default values or auto-sized by EnergyPlus.

4.5. Parameter estimation

For the case study, the tested hypothesis was 'the parameters related to building use or system operations are associated with occupancy. The heating/cooling schedule, lighting schedule, equipment schedule, occupant number, lighting load and occupant heat load could be related to occupancy schedule. First, two on-site visits were performed to collect the information about the occupancy capacity of each zone and the specifications and number of computers and appliances in each zone. It has been demonstrated by the authors' previous research that occupancy schedules could be estimated by a real-time non-intrusive occupancy detection model using the observable ambient related parameters, such as CO_2 concentration, temperature and light level [58–60]. The underlying assumption is that occupancy status regularly influences the ambient environment. Thus, there exists a relationship between presence of an occupant and changes in the ambient factors, where an occupant is present. By mathematically or statistically modeling this relationship through supervised learning, future ambient data could be analyzed to output corresponding occupancy status. The sampling rate for the occupancy detection model was 3 min. Schedules for rooms without ambient sensors were determined according to the ANSI/ASHRAE/IES Standard 90.1-2013 [61].

Equipment/appliances were assumed to be only used when a space was occupied thus their schedules followed occupants' schedules. Lighting levels were sensed by light sensors in each

Table 2c
Influential parameters and their parameter ranges and default values for the zone level energy simulation (blue-shaded parameters are for controlling the HVAC system under different ECMs, brown-shaded parameters are estimated based on observable evidence, red shaded parameters are found to be statistically insignificant in discrepancy analysis – explained in Section 4.6).

IDs	Influential Parameters	Parameter Ranges	Default Value	IDs	Influential Parameters	Parameter Ranges	Default Value
1	Solar Heat Gain Coefficient	0.25<=X<=0.8	0.5	18	Heating/Cooling Time Interval	0<=X<=60	10
2	Sensible Heat Ratio	0.5<=X<=1	0.8	19	Equipment/ Appliance Schedule	Estimable	TBD
3	Wall U-Factor	0.2<=X<=1.2	0.8	20	Minimum ~~Air Flow~~Airflow Fraction	0<=X<=1	0.2
4	Supply-Air-to-Zone-Air Temperature Difference	-20<=X<=20	6	21	Occupant Heat Load	Estimable	TBD
5	Zone Flow Coefficient	0<=X<=1	0.8	22	Zone Supply Air Temperature	50<=X<=90	68
6	Heating/Cooling Schedule	ECM control	TBD	23	Occupant Activity	100<=X<=150	115
7	Fresh Air Introduction Rate	20<=X<=50	35	24	Delta Adjacent Zone Air Temperature	-20<=X<=20	10
8	Thermostat Setpoint	ECM Control	TBD	25	Daily Temperature Range	-20<=X<=20	10
9	Zone Cooling Sizing Factor	0<=X<=5	1.1	26	Solar Transmittance	0<X<1	0.7
10	Temperature Sensor Height Above Ground	0<=X<=3	1.6	27	Airflow Convergence Tolerance	0<X<1	0.0004
11	Occupancy Schedule	Estimable	TBD	28	Visible Reflectance	0<=X<=1	0.08
12	Occupant Number	Estimable	TBD	29	Infiltration Rate	0.1<X<=5	1.8
13	Delta Adjacent Zone Temp	-20<=X<=20	10	30	Light Fraction Radiant	0<=X<=1	0.72
14	Lighting Schedule	Estimable	TBD	31	Surface Albedo	0<=X<=1	0.3
15	Minimum Surface Convection Heat	0<=X<=5	3	32	Internal loads density	1.5<=X<=3	1.8
16	Airgap Thermal Resistance	X>0	0.2	33	Lighting Time Interval	0<=X<=60	10
17	Glazing Conductivity	X>0	0.9				

room. Light fixtures were assumed to be used if a space was occupied and when artificial lighting was needed during 6:30–10:00 and 15:30–18:00 (after 18:00 lighting schedules were the same as the occupancy schedules). The parameter for occupant heat load was calculated based on the occupant number at each time point and based on the standards specified by the ASHRAE 2009 [62]. The exceptional parameters controlled in this paper were for the two ECMs of HVAC setpoint controls and are presented in Tables 2a–2c. The two parameters of HVAC Setpoints and Heating/Cooling Schedules for the 14 zones during the bimodal ECM implementation period were programmed and driven by actual occupancy; otherwise they followed the baseline ECM. Occupancy of a particular zone was determined by aggregating the occupancy of associated rooms. A zone was considered vacant only if all rooms within the zone were vacant.

4.6. Simulation discrepancy analysis

Matlab was used in this study to implement the discrepancy analysis and discrepancy minimization for calculating the values of adjustable parameters. In this case study, there were 29 adjustable parameters for the building level simulation, 24 adjustable parameters for ECM level simulation, and 26 adjustable parameters for zone level simulation (see unshaded and red-shaded parameters in Tables 2a–2c), which were assumed to be responsible for the majority of the discrepancy between the simulated and measured energy consumption. This step analyzed where the major errors lied based on a regression fitting by weighing the relations $\widehat{Y}_{\text{building level}} = a_0 + a_1X_1 + a_2X_2 + \ldots + a_{29}X_{29} + \varepsilon_{\text{building level}}, \widehat{Y}_{\text{ECM level}} = b_0 + b_1Z_1 + b_2Z_2 + \ldots + b_{24}Z_{24} + \varepsilon_{\text{ECM level}}$ and $\widehat{Y}_{\text{zone level}} = c_0 + c_1Z_1 + c_2Z_2 + \ldots + c_{26}Z_{26} + \varepsilon_{\text{zone level}})$ and testing the statistical significance. Specifically, $\widehat{Y}_{\text{level } i}$ is the simulation discrepancy at the i level, $a_0,\ b_0,\ c_0$ are the constant, $a_n,\ b_n,\ c_n$ are the coefficients for regression respectively, and ε_i is the residual of the regression function for level i simulation. Actual energy consumption data, collected from January 1st to March 10th, were used for the multi-regression analysis, and the results were presented in Figs. 7–9.[2] Each adjustable parameter was normalized within [0,1]. Random sampling was used to select the samples within the predefined parameter ranges to form the independent variables. The partial regression coefficients and intercepts were calculated with the method of least square. The larger the calculated coefficient is, the more contribution a parameter has to the discrepancy. If a certain parameter has no significant influence in a multi-linear regression formula, its coefficient was given the value of

[2] For interpretation of color in Figs. 7–9 and Tables 2a–2c, the reader is referred to the web version of this article.

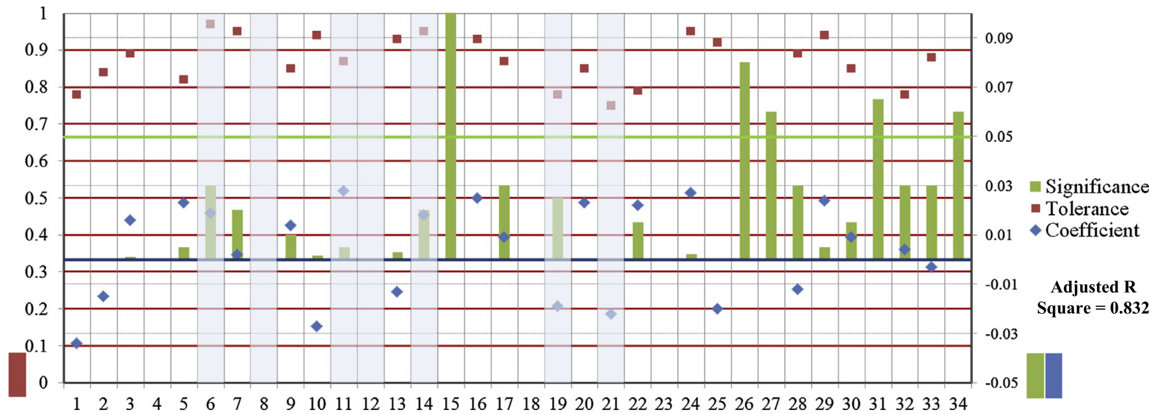

Fig. 7. Multi-regression analysis results at the building level ($F = 57.24$) – See Table 2a for parameter IDs (Estimable parameters and ECM control related parameters are shaded).

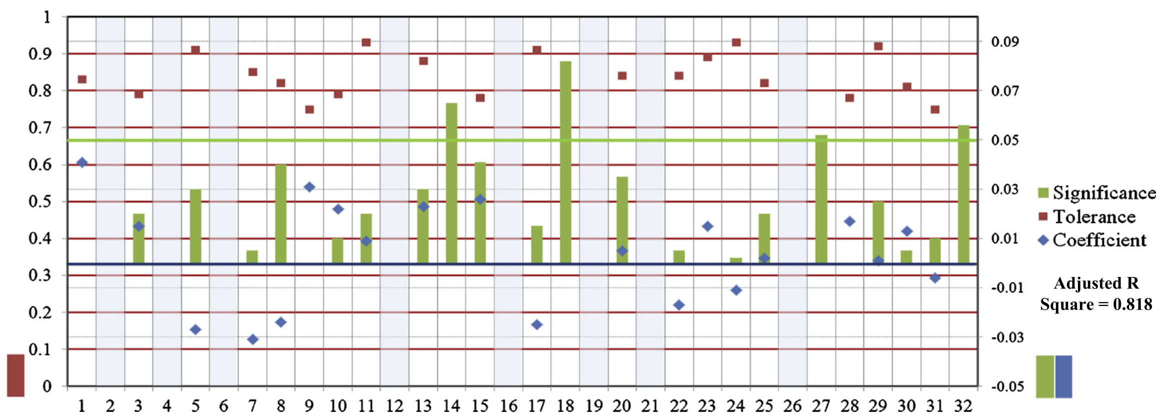

Fig. 8. Multi-regression analysis results at the ECM level ($F = 32.16$) – See Table 2b for parameter IDs (Estimable parameters and ECM control related parameters are shaded).

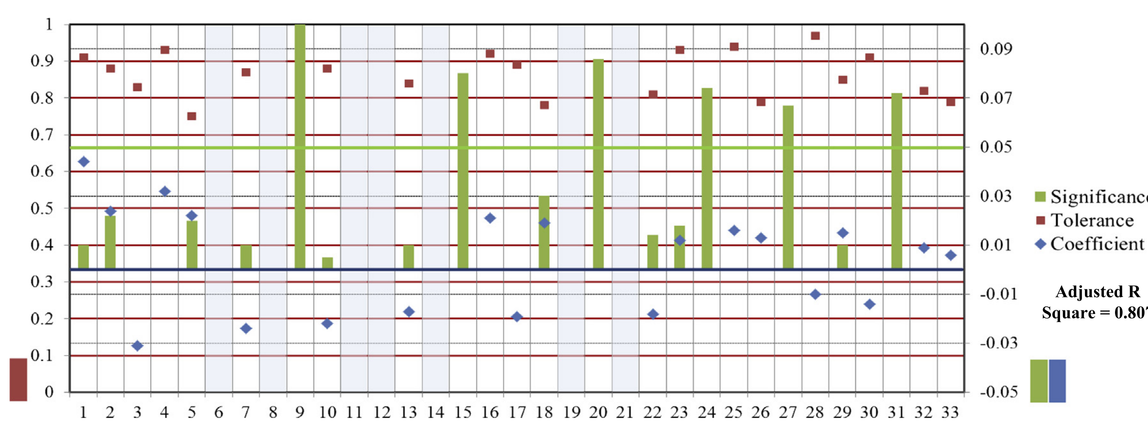

Fig. 9. Multi-regression analysis results at the zone level ($F = 41.59$) – See Table 2c for parameter IDs (Estimable parameters and ECM control related parameters are shaded).

0. A positive coefficient (above blue lines) indicates an overestimation, while a negative (below blue lines) indicates an underestimation in the simulated results (Figs. 7–9). The results showed that a parameter with high influence on simulation results in the sensitivity analysis does not mean high influence on simulation discrepancy in the regression analysis.

The two criteria for analyzing the influences of parameters and their mutual relations were then investigated. The first criterion is the adjusted determination coefficient (Adjusted R Square), used to represent the percentage of a dependent variable (energy simulation discrepancy) that can be explained by the independent variables (adjustable parameters). In this case study, approximately 83.2% of the building level energy discrepancy, 81.8% of the ECM level energy discrepancy, and 80.7% of the zone level energy discrepancy could be attributed to those adjustable parameters. The second criterion is the tolerance for the multicollinearity between the parameters. The smaller the tolerance value is, the stronger the multicollinearity appears. The results also demonstrated that significant adjustable parameters were all independent at all the three levels (red dots in Figs. 7–9).

Similar to the conclusion in the sensitivity analysis that there was no parameter interaction and all the adjustable parameters were linearly related to the simulation discrepancy. In addition, the significance tests (at a 95% confidence level) for assessing statistical significance of multi linear regression equations and coefficients were also explored. *F*-test results (Figs. 7–9) showed the three multi linear regression equations all had *F* values larger than the critical values ($F_{\text{building}} = 1.47$, $F_{\text{ECM}} = 1.52$, $F_{\text{zone}} = 1.82$), demonstrating the regression models were statistically significant and the simulation discrepancies were mainly impacted by the adjustable parameters. Based on the *T*-test results except for the parameters of Solar Heat Gain Coefficient (ID# 15), Fresh Air Introduction Rate (ID# 26), Maximum Zone Wind Speed (ID# 27), Ground Temperature (ID# 31), and Reference Barometric Pressure (ID# 34) in building level regression, the parameters of Supply-Air-to-Zone-Air Temperature Delta (ID# 14), Fraction of Convective Internal Loads (ID# 18), Effective Air Leakage Area (ID# 27) and Visible Absorptance (ID# 32) in ECM level regression, and the parameters of Zone Cooling Sizing Factor (ID# 9), Minimum Surface Convection Heat (ID# 15), Minimum Airflow Fraction (ID# 20), Delta Adjacent Zone Air Temperature (ID# 24), Airflow Convergence Tolerance (ID# 27) and Surface Albedo (ID# 31), the coefficients of other individual parameters were all statistically significant (green lines in Figs. 7–9), indicating the insignificant parameters are successfully differentiated from significant parameters (Tables 2a–2c), which account for the simulation discrepancy.

4.7. Simulation discrepancy minimization

Statistically significant parameters were processed by multi-objective programming to determine the values within value ranges that could minimize the simulation discrepancies. The energy consumption data from January 1st to March 10th 2013 were used for model calibration, while the data from March 15th to November 15th 2014 were used for evaluating the performance of multiple-level simulation calibration (objective 1), and the data from March 11st to April 28th 2013 were used for evaluating the model robustness by mixing the ground truth of two ECMs (objective 2) (Fig. 10). In this case study, hourly simulation was conducted and hourly tolerances (from IPMVP, FEMP and ASHRAE) were used for evaluating daily MSE and CV (RMSE). For objective 1, one month was used as the period for calculating the hourly MBE and CV (RMSE); for objective 2, seven days (one week) were considered as one period for calculating the hourly MBE and CV (RMSE). Specifically, the data for calibration (from January 1st to March 10th) were used for generating solutions and choosing the weights for discrepancies at three levels. With different preferences, different combinations of weight values were searched iteratively until the weighted discrepancies converged (Table 3).

Six possible combinations of weights were tested for building level preferred optimization, ECM level preferred optimization and zone level preferred optimization. However, the different preferences did not converge to the same result in this case study. A possible reason could be that one level simulation accuracy had a conflict with another. Since each objective function has its own parameters that do not exist in another objective function, different weight preferences that are assigned to the three functions may result in different solutions for those parameters. Solutions are the sets of values for parameters that could minimize either the objective functions (building level, ECM level, or zone level) or the weighted objective function. There might be one or multiple solutions as different combinations of values may achieve the same results. Based on the results in Table 3, ECM level preferred solutions (3rd combination with the relative preference of ECM level > zone level > building level) could achieve lower simulation discrepancy and converge faster. ($w_{\text{building}} = 0.27$, $w_{\text{ECM}} = 0.39$; $w_{\text{zone}} = 0.34$) was selected for further evaluation. Linear programming was then used to find the initial solution. The effective solutions were also searched and the corresponding function outputs were then compared to conclude which solution could minimize weighted simulation discrepancy.

To illustrate the difference in estimation of parameters at different levels and how they are eventually combined into one model, the following example is provided. After the initial modeling (Step 1), for example, if Wall U-factor existed in the lists of influential parameters for all three levels based on the sensitivity analysis (Step 2), it was considered to significantly contribute to the accuracy of the final model at the building level, ECM level and the zone

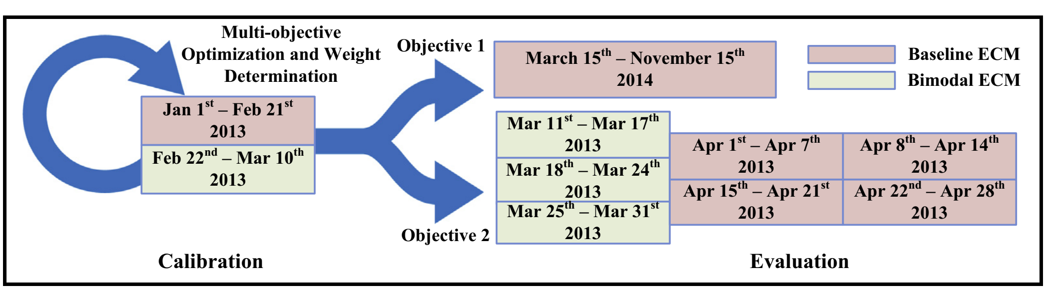

Fig. 10. Data collection periods for energy model calibration and evaluation.

Table 3
The convergence results (weights, weighted discrepancy and iterations) for different combinations of preferred weights.

Preference Combination	Building Level	ECM Level	Zone Level	Weighted Discrepancy (%)	Iterations
1	0.51	0.32	0.17	7.3	187
2	0.56	0.2	0.24	8.1	212
3	0.27	0.39	0.34	5.7	115
4	0.29	0.49	0.22	6.8	132
5	0.21	0.33	0.46	6.2	156
6	0.25	0.23	0.52	7.4	183

level. Since this parameter cannot be calculated by parameter estimation (Step 3), it is an adjustable parameter and should be determined by discrepancy analysis (Step 4) and discrepancy minimization (Step 5). After decomposing the discrepancies between the simulated and actual energy performances to the adjustable parameters, if Wall U-factor was statistically significant for contributing to the simulation discrepancies at all three levels, its weight for either of the three levels of simulation discrepancy can be recognized through a regression analysis. Multi-objective optimization was then conducted to find the final value of U-factor that could synergize with other parameters to minimize weighted simulation discrepancies of the three levels. Its varying values should be limited within its parameter ranges and are recommended not to be far from the default values set in Energyplus.

5. Validation results and discussion

To evaluate the performance of the calibrated building model at multiple levels, eight months' data from March 15th 2014 to November 15th 2014 were collected for validating multi-level simulation accuracy, and the results were shown in Figs. 11 and 12.

In general, the calibrated model could simulate long-term energy consumption with an absolute hourly error (MBE value) below 8.1% (6.9% for average) at the building level, below 7.8% (7.1% for average) at the ECM level, and below 8.5% (7.7% for average) at the zone level for all of the tested months. MBE values were slightly lower than the CV (RMSE) values. One explanation could be that simulation overestimation might be compensated by the underestimation. The variations of the simulation discrepancy were not significant (12.2% for average at the building level, 11.1% for average at the ECM level and 12.8% for average at the zone level). All of the CV (RMSE) values were within the tolerances regulated by the ASHRAE, FEMP and IPMVP. As the evaluation results (test performance) were consistent with the calibration results (training performance) in Table 3, the calibrated model was not overfit. The results also demonstrated the consistency of calibrated building energy model over time and season.

Based on the results, the modeled thermal characteristics may not fit the actual characteristics of the building so well, as the energy model overestimated the energy consumption at all of the three levels when there was not much cooling required (March to May and October to November). However, during the seasons where cooling was required (May to October), the building level simulation tended to underestimate the energy consumption, possibly because the performances of HVAC plants and systems were overestimated to be more energy efficient than they were in reality. Meanwhile, ECM level simulation may underestimate the control inefficiency and it may also lack the consideration of thermal influences of the adjacent spaces controlled by another AHU. Zone level simulation assumed to have less space heat gains than the actual end use demand and was influenced by the overestimated HVAC system performance as the outside temperature increased. Since not all the zones were selected for calibration and only average zone energy consumption was considered, simulation results for individual zones may deviate from the measured energy consumption, resulting in zone level simulation to be higher in MBE and CV (RMSE) compared to the ECM level and the building level simulation.

In order to explore whether the energy model calibrated using ground truth energy data from mixed ECMs, could consistently simulate energy performance for each ECM, the period from March 11st to April 30th was selected for evaluation of the second objective, during which three weeks were operated by the bimodal ECM in the 14 zones and the rest were operated by the baseline ECM. The corresponding MBE values and CV (RMSE) values were calculated at the ECM level and presented for comparing the simulated results with actual energy performance (Fig. 13). It can be concluded that the hypothesis should be accepted that energy model calibrated under two ECMs could consistently simulate actual energy consumption under either ECM independently.

At the ECM level, the differences of averaged MBE between baseline ECM and bimodal ECM were 0.7% (with the absolute difference below 1.8% between any pair), and the averaged differences of CV (RMSE) were 0.4% (with the difference below 1.9% between any pair), which indicated that the calibrated model

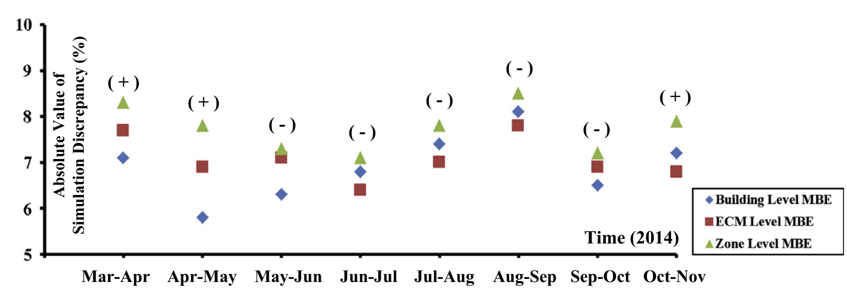

Fig. 11. MBE values for the calibrated model.

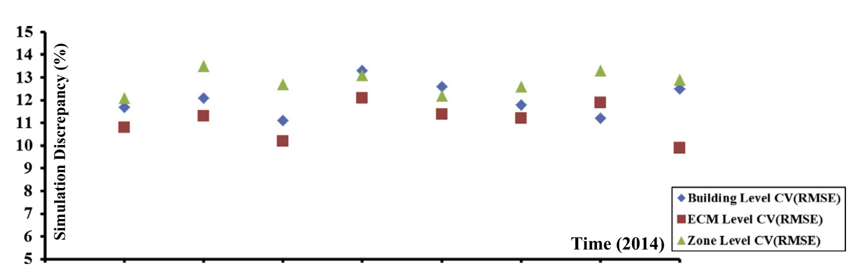

Fig. 12. CV (RMSE) values for the calibrated model.

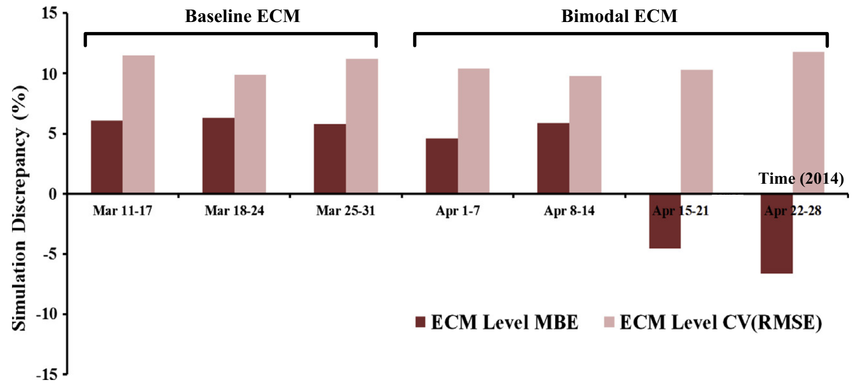

Fig. 13. MBE values and CV (RMSE) values for the calibrated model at the ECM level.

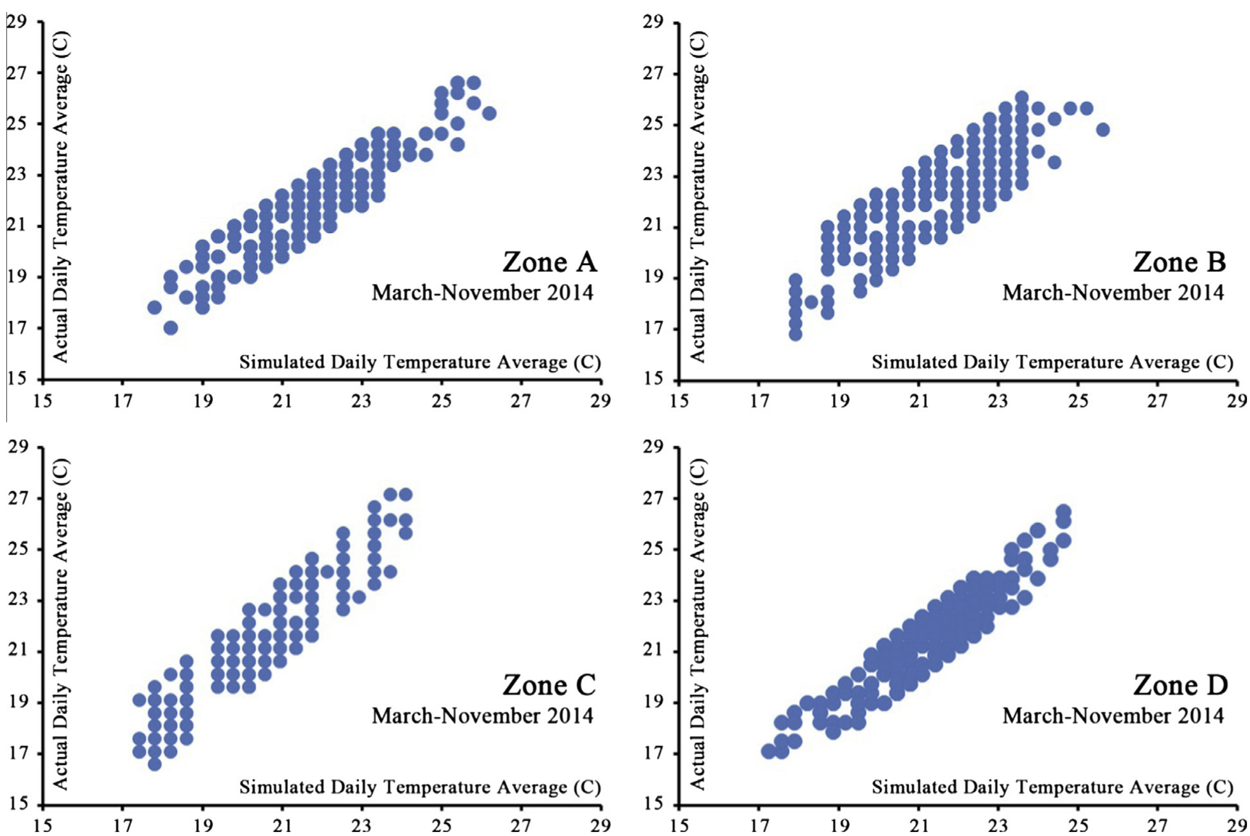

Fig. 14. Comparison of simulated temperature and actual temperature for randomly selected four zones.

was robust enough to the changes resulting from the building being operated differently.

In order to evaluate the quality of simulation for thermal conditions, four zones in the case study building were randomly selected. For each zone, the comparisons between simulated average daily temperatures and actual average daily temperatures from March 15th to November 15th were presented in Fig. 14. Since all the points were closely around the line $y = x$ (average absolute value is 2.1 °C for Zone A, 2.7 °C for Zone B, 3.1 °C for Zone C and 1.9 °C for Zone D), the comparison results demonstrated that the thermal conditions were well simulated by the calibrated energy model.

Summarily, the actual calibration process guided by the proposed calibration framework used evidence and statistical learning steps. Evidence was used to build the energy model and statistical learning was used to reduce the simulation discrepancy. The propose calibration framework does not need retraining when changes are made to building conditions, operations and conservation measures; meanwhile it avoids the trial-and-error process, which requires significant time, effort and expertise. The presented framework is a generalizable method, which is not specific to any building type or building system type. Although EnergyPlus was used as the simulation program to validate the calibration method, the method is not designed for EnergyPlus and could be used with other simulation programs.

However, the study bears certain limitations, which should be investigated in future research. First, the parameter ranges used were kept unchanged during the calibration process, which should be updated continuously to reduce the searching workload and improve the accuracy of parameter value determination; however, this was not within the scope of this paper. Second, in sensitivity analysis the joint-effects of input parameters on energy simulation results were not systematically considered because the rankings of parameters were sufficient to differentiate the influential parameters. Other global sensitivity algorithms such as extended Fourier Amplitude Sensitivity (EFAST) could be used to investigate the correlations among these parameters. Third, a linear relationship was assumed between adjustable parameters and simulation discrepancy as a start. The patterns of simulation discrepancies have not been systematically analyzed. Later, other relationships such as non-linear, fuzzy or statistical fitting could also be tested. Fourth, in discrepancy minimization, if there are many common parameters in multiple objectives, it becomes challenging to find the optimum solution that simultaneously minimizes all of the objectives. In addition, the introduction of more constraints may increase the difficulty of finding feasible solutions. Other optimization approaches could also be explored. Fifth, the actual energy data collection period was only for cooling-dominant seasons, as in Southern California, cooling is dominant function of an HVAC system and the model performance for heating-dominant seasons and other climate zones should also be studied. Lastly, there are several thousands of input parameters but relatively a small number of output results, several solutions may meet the criteria at the same time and it is difficult to select the appropriate one to determine the values of input parameters. More targeted criteria are required, and the energy consumption should be metered at more detailed levels for more precise energy model calibration.

6. Conclusions

Building energy performance analysis using energy simulations could help researchers and practitioners to identify relatively optimal energy conservation measures in existing buildings. A well-calibrated model is crucial to accurately represent a building and provide confidence and reliability in potential energy savings, enabled by the conservation measures, especially when field experiments for testing all ECMs are infeasible. In particular, a building energy simulation model should have high accuracies at multiple levels for different purposes. In addition, multiple levels of accuracies are interconnected and they reflect the level of approximation of simulation results to measured energy performance. However, current calibration methods focus on single-level simulation accuracy, either at the building level or at the zone level. Accurate simulation of single level does not necessarily mean accurate simulations for other levels especially when there are several zones and multiple HVAC units.

This paper introduced a multi-level calibration framework to improve the accuracy of building energy simulation models at multiple levels. Evidence-available parameters are identified and linked to the physical building characteristics, system properties and environmental conditions, while the remaining parameters are identified as main sources for discrepancies between the simulated and measured energy performances. A classification schema was created to classify all of the input parameters into hieratical categories for analyzing and determining the values of the parameters without direct evidence. An optimization solution was used to minimize discrepancies and achieve simultaneously high calibration accuracy. The calibration framework followed five steps: (1) initial energy modeling using available evidence to reproduce building energy behavior; (2) sensitivity analysis for ranking the influence of each parameter on energy simulation results at multiple levels; (3) parameter estimation for determining the values of estimable parameters; (4) discrepancy analysis to explain the discrepancies between simulated and actual energy performances based on regression fitting; and (5) discrepancy minimization for determining the values of parameters to minimize the discrepancies between simulation and measured energy performance by multi-objective programming.

A case study was used to evaluate the validity of the proposed framework. Simulated HVAC-related energy consumption was compared with the measured HVAC-related energy consumption of the building. The results showed that MBE and CV (RMSE) for all of the test weeks were below 8.5% and 13.5%, which demonstrated that the proposed framework could accurately calibrate energy simulation model at building level, ECM level and zone level. Considering the fact that energy simulation is mainly used to estimate expected energy savings from different energy conservation measures (ECMs), the energy model should be robust to the changes resulting from building being operated under different control strategies. In order to assess the credibility of expected energy savings resulting from buildings being operated differently, the ground truth energy data used for calibration were collected for the periods when two different energy conservation measures were implemented. The calibrated model had less than 2% absolute difference between the baseline ECM and bimodal ECM for both MBE and CV (RMSE) at ECM level, demonstrating the robustness of the calibrated model to predict the performances of both measures.

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References

[1] International Energy Agency. Transition to Sustainable Buildings-Strategies and Opportunities to 2050. Paris (France); 2013.
[2] United Nations Environment Programme. Buildings can play key role in combating climate change. SBCI-Sustainable Construction and Building Initiative. Updated:2007. <http://www.unep.org/Documents.Multilingual/Default.Print.asp>. [accessed 01.13].
[3] Energy Information Administration. Annual Energy Outlook 2012 with Projections to 2035. United States; 2012.
[4] Široký J, Oldewurtel F, Cigler J, Prívara S. Experimental analysis of model predictive control for an energy efficient building heating system. Appl Energy 2011;88(9):3079–87.
[5] Pisello AL, Goretti M, Cotana F. A method for assessing buildings' energy efficiency by dynamic simulation and experimental activity. Appl Energy 2012;97:419–29.
[6] Huang Y, Niu J, Chung T. Study on performance of energy-efficient retrofitting measures on commercial building external walls in cooling-dominant cities. Appl Energy 2013;103:97–108.
[7] Raftery P, Keane M, Costa A. Calibrating whole building energy models: detailed case study using hourly measured data. Energy Build 2011;43(12):3666–79.
[8] Mustafaraj G, Marini D, Costa A, Keane M. Model calibration for building energy efficiency simulation. Appl Energy 2014;130:72–85.
[9] Ahmad M, Culp CH. Uncalibrated building energy simulation modeling results. HVAC&R Res 2006;12(4):1141–55.
[10] Heo Y, Choudhary R, Augenbroe G. Calibration of building energy models for retrofit analysis under uncertainty. Energy Build 2012;47:550–60.
[11] Manfren M, Aste N, Moshksar R. Calibration and uncertainty analysis for computer models-A meta-model based approach for integrated building energy simulation. Appl Energy 2013;103:627–41.
[12] Menezes AC, Cripps A, Bouchlaghem D, Buswell R. Predicted vs. actual energy performance of non-domestic buildings: using post-occupancy evaluation data to reduce the performance gap. Appl Energy 2012;97:355–64.
[13] Booth A, Choudhary R, Spiegelhalter D. A hierarchical Bayesian framework for calibrating micro-level models with macro-level data. J Build Perform Simulat 2013;6(4):293–318.
[14] Stéphane Bertagnolio. Evidence-based model calibration for efficient building energy servicesUniversité de Liège, Liège, Belgium; 2012.
[15] Trčka M, Hensen JL. Overview of HVAC system simulation. Autom Constr 2010;19(2):93–9.

[16] Hong TZ. Data and analytics to inform energy retrofit of high performance buildings. Appl Energy 2014;126(1):90–106.
[17] Rahman MM, Rasul M, Khan MMK. Energy conservation measures in an institutional building in sub-tropical climate in Australia. Appl Energy 2010;87(10):2994–3004.
[18] Fumo N. A review on the basics of building energy estimation. Renew Sustain Energy Rev 2014;31:53–60.
[19] Coakley D, Raftery P, Keane M. A review of methods to match building energy simulation models to measured data. Renew Sustain Energy Rev 2014;37:123–41.
[20] Magnier L, Haghighat F. Multiobjective optimization of building design using TRNSYS simulations, genetic algorithm, and Artificial Neural Network. Build Environ 2010;45(3):739–46.
[21] Sun J, Reddy TA. Calibration of building energy simulation programs using the analytic optimization approach (RP-1051). HVAC&R Res 2006;12(1):177–96.
[22] Liu Simeng, Henze G. Calibration of building models for supervisory control of commercial buildings. Proceedings of the 9th international building performance simulation association (IBPSA) conference. Montreal (Canada); 2005.
[23] Kalogirou SA. Applications of artificial neural-networks for energy systems. Appl Energy 2000;67(1):17–35.
[24] Pao H. Comparing linear and nonlinear forecasts for Taiwan's electricity consumption. Energy 2006;31(12):2129–41.
[25] Amjady N. Short-term hourly load forecasting using time-series modeling with peak load estimation capability. Power Syst, IEEE Trans 2001;16(3):498–505.
[26] Neto AH, Fiorelli FAS. Comparison between detailed model simulation and artificial neural network for forecasting building energy consumption. Energy Build 2008;40(12):2169–76.
[27] Karunakaran R, Iniyan S, Goic R. Energy efficient fuzzy based combined variable refrigerant volume and variable air volume air conditioning system for buildings. Appl Energy 2010;87(4):1158–75.
[28] Jibonananda Sanyal, Joshua New, Richard Edwards. Supercomputer assisted generation of machine learning agents for the calibration of building energy models. In: Proceedings of the conference on extreme science and engineering discovery environment: gateway to discovery. ACM; 2013.
[29] Shapiro I. Energy audits in large commercial office buildings. ASHRAE J 2009;51(1):18.
[30] Westphal FS, Lamberts R. Building simulation calibration using sensitivity analysis. Build Simulat 2005;9:1331–8.
[31] Zhou D, Park SH. Simulation-assisted management and control over building energy efficiency-a case study. Energy Procedia 2012;14:592–600.
[32] Fumo N, Mago P, Luck R. Methodology to estimate building energy consumption using EnergyPlus Benchmark Models. Energy Build 2010;42(12):2331–7.
[33] Zhou X, Zhu Y, Xia C, Chen H. Simulation-based method to assess building energy consumption level at operation stage. Beijing (China): International Building Performance Simulation Association; 2007.
[34] Monfet D, Charneux R, Zmeureanu R, Lemire N. Calibration of a building energy model using measured data. ASHRAE Trans 2009;115(1).
[35] Parker J, Cropper P, Shao L. A calibrated whole building simulation approach to assessing retrofit options for Birmingham Airport. Building Simulation and Optimization. UK: Loughborough; 2012.
[36] Pan Y, Huang Z, Wu G. Calibrated building energy simulation and its application in a high-rise commercial building in Shanghai. Energy Build 2007;39(6):651–7.
[37] Yoon J, Lee E, Claridge D. Calibration procedure for energy performance simulation of a commercial building. J Solar Energy Eng 2003;125(3):251–7.
[38] Chakrit Bhamornsiri, Patricia Gomez, Tyler Wilson, Bryan Eisenhower. Calibration of envelope parameters using control-based heat balance identification and uncertainty analysis. In: Proceedings of BS2013: 13th conference of international building performance simulation association. Chambéry (France); 2013.
[39] Struck C, Hensen J, Kotek P. On the application of uncertainty and sensitivity analysis with abstract building performance simulation tools. J Build Phys 2009;33(1):5–27.
[40] Eisenhower B, O'Neill Z, Fonoberov VA, Mezić I. Uncertainty and sensitivity decomposition of building energy models. J Build Perform Simulat 2012;5(3):171–84.
[41] Lomas KJ, Eppel H. Sensitivity analysis techniques for building thermal simulation programs. Energy Build 1992;19(1):21–44.
[42] Reddy TA, Maor I, Panjapornpon C. Calibrating detailed building energy simulation programs with measured data-Part I: general methodology (RP-1051). Hvac&R Res 2007;13(2):221–41.
[43] O'Neill Z, Eisenhower B, Fonoberov V, Bailey T. Calibration of a building energy model considering parametric uncertainty. ASHRAE Trans 2012;118(2).
[44] Coakley D, Raftery P, Molloy P, White G. Calibration of a detailed BES model to measured data using an evidence-based analytical optimisation approach. Building simulation and optimization. UK: Loughborough; 2012.
[45] Saltelli A, Tarantola S, Campolongo F. Sensitivity analysis as an ingredient of modeling. Stat Sci 2000:377–95.
[46] De Wit S, Augenbroe G. Analysis of uncertainty in building design evaluations and its implications. Energy Build 2002;34(9):951–8.
[47] Morris MD. Factorial sampling plans for preliminary computational experiments. Technometrics 1991;33(2):161–74.
[48] Oldewurtel F, Sturzenegger D, Morari M. Importance of occupancy information for building climate control. Appl Energy 2013;101:521–32.
[49] Azar E, Menassa CC. A comprehensive analysis of the impact of occupancy parameters in energy simulation of office buildings. Energy Build 2012;55:841–53.
[50] Nguyen A, Reiter S, Rigo P. A review on simulation-based optimization methods applied to building performance analysis. Appl Energy 2014;113:1043–58.
[51] Coello Coello CA. Evolutionary multi-objective optimization: a historical view of the field. Computat Intell Magaz, IEEE 2006;1(1):28–36.
[52] Loris I, Bertero M, De Mol C, Zanella R, Zanni L. Accelerating gradient projection methods for ℓ1-constrained signal recovery by step length selection rules. Appl Comput Harmon Anal 2009;27(2):247–54.
[53] NREL. OpenStudio: Commercial Buildings Research and Software Development. Updated:2013. <http://openstudio.nrel.gov/>. [accessed 30.09.13].
[54] ASHRAE. Guideline 14–2002, Measurement of Energy and Demand Savings. American Society of Heating, Ventilating, and Air Conditioning Engineers, Atlanta, Georgia; 2002.
[55] Energy, Determining, and Water Savings. International performance measurement & verification protocol. Energy Project Financing: Resources and Strategies for Success Lilburn, GA: The Fairmont Press, Inc.; 2009.
[56] Federal Energy Management Program (FEMP). M&V Guidelines: Measurement and Verification for Federal Energy Projects; 2008.
[57] Energy Efficiency and Renewable Energy. EnergyPlus Energy Simulation Software: Weather Data. Updated:2014. <http://apps1.eere.energy.gov/buildings/energyplus/weatherdata_about.cfm>. [accessed 12.01.14].
[58] Zheng Yang, Nan Li, Burcin Becerik-Gerber, Michael Orosz. A non-intrusive occupancy monitoring system for demand driven HVAC operations. Construct Res Congress 2012:828–37.
[59] Zheng Yang, Nan Li, Burcin Becerik-Gerber, Michael Orosz. A multi-sensor based occupancy estimation model for supporting demand driven HVAC operations. In: Proceedings of the 2012 Symposium on Simulation for Architecture and Urban Design. Society for Computer Simulation International; 2012.
[60] Yang Z, Li N, Becerik-Gerber B, Orosz M. A systematic approach to occupancy modeling in ambient sensor-rich buildings. Simulation 2013. http://dx.doi.org/10.1177/0037549713489918.
[61] ASHRAE, ANSI and IES. ANSI/ASHRAE/IES Standard 90.1-2013 Energy Standard for Buildings Except Low-Rise Residential Buildings; 2013.
[62] ASHRAE. Standard 189.1-2009, Standard for the Design of High-Performance Green Buildings Except Low-Rise Residential Buildings. American Society of Heating, Refrigerating and Air-Conditioning Engineers, Atlanta, GA; 2009.